

AN INTEGRATED FRAMEWORK FOR TYPHOON-INDUCED AGRICULTURAL LOSS ACROSS MULTIPLE CROPS

UN CADRE INTÉGRÉ D'ÉVALUATION DES PERTES AGRICOLES DUES AUX TYPHONS POUR PLUSIEURS CULTURES

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ABSTRACT

Agricultural security is fundamental to food resource stability; however, it remains highly vulnerable to typhoon-induced hazards. While existing research predominantly focuses on major staple crops, the diverse agricultural landscape of Taiwan requires a more comprehensive multi-target assessment framework. This study develops an innovative framework to predict monetary losses across five distinct crop categories (rice, fruit trees, vegetables, grains, and flowers) using an integrated CNN-ConvLSTM model. To capture complex meteorological features, we developed the Typhoon Intensity and Type Comprehensive Index (TITCI), a PCA-based method that decouples typhoon characteristics into intensity and hazard-type dimensions. The model effectively maps spatiotemporal typhoon evolution to localized damage magnitudes across 19 counties. Quantitative evaluation demonstrates that the model achieves a test mean absolute error (MAE) of 1.4290 in log-transformed space. For event-level risk prioritization, the framework yields a high Spearman's rank correlation coefficient (ρ) of 0.7842 ($p = 0.0001$). Crucially, during catastrophic events like Typhoon MORAKOT (2009), the model achieves exceptionally high spatial Pearson correlation coefficients (r) across all five crop categories simultaneously. Furthermore, the framework also successfully generates continuous hazard fields that reveal previously potential unrecorded risk zones. By translating log-space estimations back into monetary scales via a post-calibration factor, this study provides an actionable baseline tool for early warning systems, enabling data-driven disaster management and strategic resource allocation.

Keywords: Integrated framework; Agricultural security; Monetary losses; Early warning systems; Resource allocation.

RÉSUMÉ

La sécurité agricole est fondamentale pour la stabilité des ressources alimentaires ; elle reste toutefois très vulnérable aux risques provoqués par les typhons. Alors que les recherches existantes portent principalement sur les grandes cultures vivrières de base, la diversité du paysage agricole taïwanais exige un cadre d'évaluation multi-cibles plus complet. Cette étude développe un cadre innovant permettant de prévoir les pertes monétaires dans cinq catégories de cultures distinctes — riz, arbres fruitiers, légumes, céréales et fleurs — à l'aide d'un modèle intégré CNN-ConvLSTM. Afin de représenter des caractéristiques météorologiques complexes, nous avons mis au point l'indice global d'intensité et de type de typhon (TITCI), une méthode fondée sur l'analyse en composantes principales (PCA) qui décompose les caractéristiques des typhons en deux dimensions : l'intensité et le type de danger. Le modèle établit efficacement le lien entre l'évolution spatiotemporelle des typhons et l'ampleur localisée des dommages dans 19 comtés. L'évaluation quantitative montre que le modèle atteint une erreur absolue moyenne (MAE) de test de 1,4290 dans l'espace transformé logarithmiquement. Pour la hiérarchisation des risques au niveau des événements, le cadre produit un coefficient élevé de corrélation des rangs de Spearman (ρ), de 0,7842 ($p = 0,0001$). Fait essentiel, lors d'événements catastrophiques tels que le typhon MORAKOT (2009), le modèle atteint simultanément des coefficients de corrélation spatiale de Pearson (r) exceptionnellement élevés dans les cinq catégories de cultures. En outre, le cadre génère également avec succès des champs de danger continus qui révèlent des zones de risque potentielles jusque-là non répertoriées. En reconvertissant

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les estimations dans l'espace logarithmique en valeurs monétaires au moyen d'un facteur de post-étalonnage, cette étude fournit un outil de référence directement exploitable pour les systèmes d'alerte précoce, permettant une gestion des catastrophes fondée sur les données et une allocation stratégique des ressources.

Mots clés : Cadre intégré; Sécurité agricole; Pertes monétaires; Systèmes d'alerte précoce; Allocation des ressources.

1. INTRODUCTION

Typhoons represent the primary meteorological threat to Taiwanese crop yields due to the compound impacts of high-velocity winds and intense rainfall (Li-Wei, 2018; Moh & Yao, 2005; Su et al., 2024; Yang & Chang, 2025; Yao et al., 2024). On average, Taiwan is affected by three to four typhoons annually (Wu & Kuo, 1999). Furthermore, the residual effects often persist beyond the initial typhoon departure; for instance, trailing southwesterly flow can trigger even more severe precipitation, leading to catastrophic secondary agricultural damage (Chien et al., 2008). Traditional administrative typhoon definitions often fail to encompass the full extent of trailing moisture. To address this, we integrated track-based proximity with precipitation-based thresholds to establish physically consistent hazard exposure windows, ensuring that the entire lifecycle of the hazard is comprehensively captured.

Climate change has intensified the frequency and severity of these disasters, significantly escalating agricultural losses (Ho et al., 2018; Huang et al., 2020; Hwang et al., 2024; Mall et al., 2017). For instance, recent catastrophic events such as Typhoon GAEMI (2024) and Typhoon DANAS (2025) each inflicted over 30 billion TWD (approx. 930 million USD) in damages, devastating both staple grains and high-value crops in southern Taiwan. However, existing literature predominantly focuses on staple grains (Monteleone et al., 2023), leaving a knowledge gap regarding high-value crops with varying hazard sensitivities (Baldocchi & Wong, 2008; Korres et al., 2016; Li-Wei, 2018). To address this, this study evaluates five distinct crop categories, aiming to predict the monetary loss for each category across a multi-target spatial framework.

The nature of agricultural loss corresponds to the specific characteristics of a typhoon. Rain-dominant typhoons (e.g., Typhoon KALMAEGI, 2008; TTI = -1.22) primarily damage leafy vegetables, whereas wind-dominant typhoons (e.g., Typhoon SOUDELOR, 2015; TTI = 1.83) cause catastrophic failure in crops such as bananas and pomelos which are easily blown off by strong winds (Lin, 2020). However, the existing Typhoon Type Index (TTI) has a notable limitation, it cannot evaluate the intensity of an event. A severe wind-type typhoon may yield the same TTI value as a weak one, as the index does not reflect absolute magnitude. To address this, we developed the Typhoon Intensity and Type Comprehensive Index (TITCI) based on Principal Component Analysis (PCA), providing a comprehensive metric that simultaneously accounts for both typhoon intensity and hazard type.

To provide robust climate services (Yang & Chang, 2025), neural networks have gained prominence for modeling complex, non-linear hydrological extremes (Anshuka et al., 2022; Chiang et al., 2012; Kim et al., 2024). In this study, we propose an integrated convolutional neural network (CNN) and convolutional long short-term memory (ConvLSTM) model. The ConvLSTM architecture extends the traditional LSTM by incorporating convolutional structures in both input-to-state and state-to-state transitions, effectively capturing spatiotemporal correlations (Niu et al., 2020). Such coupled models have shown success in flood forecasting by combining static geospatial features with dynamic meteorological sequences (Dunbar et al., 2026; Lou et al., 2026). Agricultural loss in Taiwan is similarly influenced by varying typhoon paths and the topography of the Central Mountain Range, which amplifies spatial differences in damage. Factors such as elevation and agricultural land distribution play decisive roles in loss patterns. While the Central Weather Administration (CWA) of Taiwan classifies typhoon path into ten clusters, this system is not specifically designed for disaster regionalization. Therefore, our study bypasses these predefined clusters and instead incorporates the continuous spatiotemporal changes as the typhoon approaches Taiwan, offering a more precise and localized estimation of agricultural vulnerability.

2. METHODOLOGY

This study establishes a systematic predictive framework for typhoon-induced agricultural loss by integrating multiscale meteorological signatures with geospatial constraints. As illustrated in the overall workflow (Figure 1), the methodology comprises four primary stages: (1) restructuring typhoon impact periods based on a union of physical criteria (T1) and track-based proximity (T2); (2) developing the TITCI to decouple and quantify atmospheric features; (3) constructing spatiotemporal tensors that align dynamic and static environmental features; and (4) implementing a CNN-ConvLSTM architecture to capture non-linear spatiotemporal correlations. Predictive magnitude and ranking accuracy are rigorously evaluated using Mean Absolute Error (MAE), Pearson Correlation Coefficient (r), and Spearman's rank correlation coefficient (ρ).

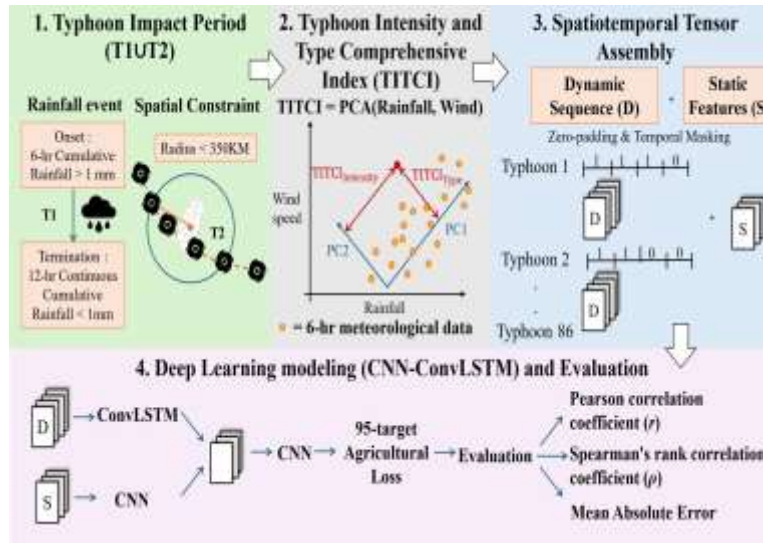


Figure 1. Proposed spatiotemporal framework for agricultural loss prediction

2.1 Restructuring precipitation-based typhoon warning periods

The core of our event definition lies in a union-based identification strategy that integrates spatial proximity with precipitation thresholds. To ensure data consistency, we adopted a 6-hour temporal resolution for Japan Meteorological Agency (JMA) best-track data. A spatial proximity threshold of 350 km from Taiwan's centroid was applied to filter impact stages, identifying 86 typhoon events between 2003 and 2023.

A precipitation-induced impact period is triggered when the 6-hour regional average rainfall exceeds 1.0 mm, and it is terminated when cumulative rainfall remains below this threshold for a continuous 12-hour window (two consecutive steps). Overlapping rainfall events and typhoon proximity periods were merged via a union operation, creating a physically consistent window that comprehensively captures the entire lifecycle from initial outer-band influences to trailing moisture.

2.2 Typhoon intensity and type comprehensive index (TITCI)

To account for Taiwan's localized meteorological characteristics, we established a site-specific baseline model for each weather station using historical 6-hour cumulative rainfall (R) and mean wind speed (W) observations captured during typhoon impact periods. Principal Component Analysis (PCA) was performed to reproject raw observations into a new orthogonal feature space, effectively decoupling synchronized typhoon intensification from relative wind-rain dominance. The resulting TITCI, enhanced from Typhoon Type index (TTI) (Lin, 2020), extracts two distinct physical attributes: (1) TITCI-Intensity (TITCI-I), defined by the projection onto the First Principal Component (PC1) to

represent the overall hazard magnitude; and (2) TITCI-Type (TITCI-T), defined by the Second Principal Component (PC2) to capture deviations from typical wind-rain correlations, where positive and negative values indicate wind-dominant and rain-dominant conditions, respectively. This PCA-based framework successfully transforms raw point observations into a dual-component feature vector [TITCI-I, TITCI-T] to simultaneously characterize the scale and nature of each typhoon event.

2.3 Spatiotemporal tensor construction via ordinary kriging

To transform point observations into a continuous spatial field suitable for deep learning architectures, we performed spatial interpolation over the main island of Taiwan. The study area was discretized into 128×128 grids, covering a latitudinal range of 21.75°N to 25.5°N and a longitudinal range of 120.0°E to 122.0°E .

We employed Ordinary Kriging (OK) to estimate the four key meteorological features (R, W, TITCI-I, and TITCI-T) for each grid cell (Wackernagel, 2003). Specifically, we utilized a linear variogram model for the kriging system. Because weather stations in Taiwan are predominantly located in coastal plains with sparse mountain coverage, a linear variogram was used to prevent unrealistic oscillations common in higher-order models, such as Gaussian or Spherical, within data-poor high-altitude zones. Moreover, we set constraints to eliminate unphysical negative values generated by the kriging variance.

For each typhoon event, the interpolated fields were stacked into a 4-dimensional spatiotemporal tensor with dimensions $T \times 128 \times 128 \times 4$, where T represents the variable duration of the typhoon impact period. Channels 1 to 4 sequentially represent 6-hour cumulative rainfall, 6-hour mean wind speed, TITCI-I (Intensity) and TITCI-T (Type) scores.

This tensorized representation preserves the spatial changes induced by typhoon's evolution, allowing the subsequent ConvLSTM-based model to learn the complex nonlinear relationships between atmospheric and agricultural damage. Finally, a land-sea mask was applied to focus the model's learning capacity exclusively on the terrestrial regions of Taiwan.

2.4 Agricultural loss data and label construction

The ground truth labels for agricultural damage used in this study were derived from the Agricultural Disaster Dataset provided by the Ministry of Agriculture, Taiwan. For multi-target regression, the raw damage data was processed into five primary crop categories: fruit, rice, vegetables, grains, and flowers. For each typhoon event, the total monetary loss (in TWD) for each category was aggregated across the 19 counties of Taiwan. This resulted in a 95-dimensional target vector (19 counties $\times$ 5 crop categories) for each event. Due to the high skewness of the loss distribution, we applied a log-transformation ($\ln(x + 1)$), to the total damage amounts. This transformation serves as the final predictive target, ensuring the model can effectively learn both minor damage and extreme loss during the training process.

2.5 CNN-ConvLSTM integrated model architecture

The comprehensive architecture of the integrated CNN-ConvLSTM model is illustrated in Figure 2, which details layer configurations, dimensions, and hyper-parameters. The model combines a ConvLSTM-based dynamic meteorological module with a CNN-based static environmental module, mapping high-dimensional spatiotemporal tensors to the 95-dimensional target vector. The architecture is partitioned into three core modules: the Typhoon Dynamics Module, the Static Feature Module, and the Spatial-Temporal Decoder. For robust evaluation, the dataset was partitioned into an independent 20% testing set and an 80% training set, the latter optimized via a stratified 5-fold cross-validation scheme (Berrar, 2019).

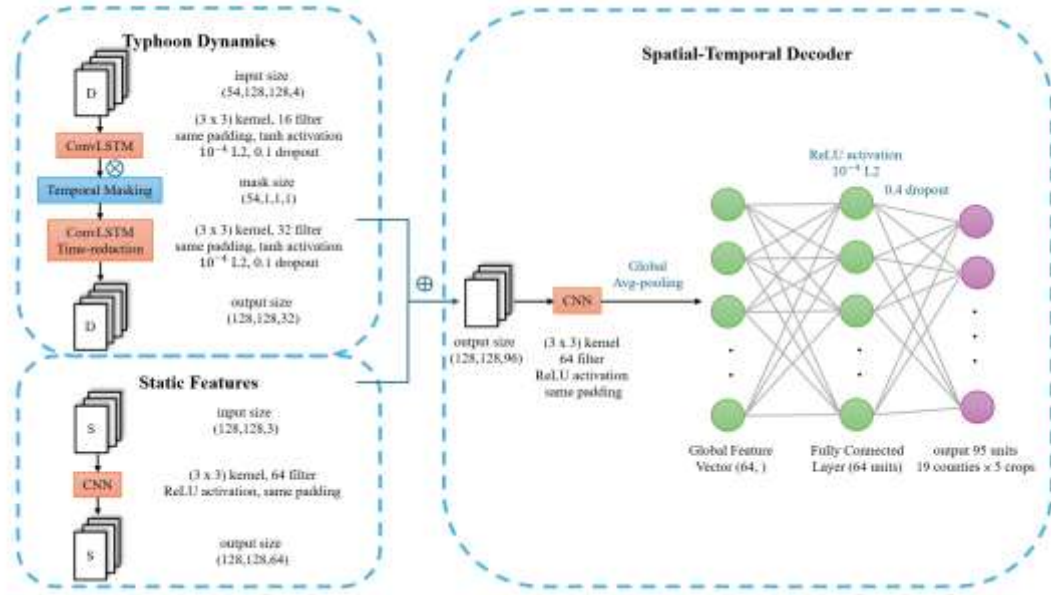


Figure 2. CNN-ConvLSTM integrated architecture with dynamic and static modules

2.5.1 Typhoon Dynamics Module

The dynamic portion of the model processes a 4-channel temporal sequence ($T \times 128 \times 128 \times 4$) comprising resampled cumulative rainfall, mean wind speed, TITCI-I, and TITCI-T. Meteorological features are normalized by historical maxima (1200 mm/6-h and 28.5 m/s) to ensure numerical stability. To manage variable event durations (T), input sequences are zero-padded to $T_{\max} = 54$, and a binary temporal mask is applied to prevent padding artifacts from distorting model learning. Two layers of Convolutional Long Short-Term Memory (ConvLSTM) are employed with 16 filters and 32 filters, respectively. The first ConvLSTM layer captures low-level features, while the second uses a time-reduction operation to extract temporal evolution.

2.5.2 Static Feature Module

Simultaneously, a parallel CNN model extracts topographic and land-use signatures from static inputs ($128 \times 128 \times 3$). These inputs include: (1) an Agricultural Area Mask derived from the Non-urban Land Use District provided by National Land Management Agency, Ministry of the Interior; (2) a normalized Digital Elevation Model (DEM) from Government Open Data Platform; and (3) a County Identification Mask to provide spatial location. A 2D-convolutional layer transforms these environmental constraints into a $128 \times 128 \times 64$ feature map using ReLU activation, batch normalization and L2 regularization (10^{-4}).

2.5.3 Spatial-temporal decoder and multi-target regression

The outputs of the dynamic and static modules are merged via a concatenation operation ($\oplus$), resulting in a fused $128 \times 128 \times 96$ tensor. The Spatial-Temporal Decoder subsequently performs feature abstraction and dimensionality reduction using a 2D-CNN layer with global average pooling to extract representative regional features. The flattened vector is passed through a fully connected layer (64 units) with L2 regularization (10^{-4}) and a 0.4 dropout rate to enhance generalization. Finally, the output layer utilizes 95 neurons with a ReLU activation function to ensure non-negative log-damage predictions, optimized via the Huber loss function.

2.6 Statistical evaluation

To assess the predictive performance of the CNN-ConvLSTM model, we employed Mean Absolute Error (MAE) to quantify the deviation between the predicted and actual monetary values, Pearson Correlation Coefficient (r) to evaluate the spatial accuracy of the model and Spearman's Rank Correlation Coefficient (ρ) to evaluate the monotonic relationship. The Pearson correlation is defined as

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (y_i - \bar{y})^2}}$$

3. RESULTS

3.1 Spatiotemporal reconstruction of typhoon impact periods and TITCI signatures

The union of track-based and precipitation thresholds successfully identified extended impact windows. As demonstrated in Figure 3, this reconstruction effectively captures preceding rainfall bands and trailing moisture, such as southwesterly flows, which are critical contributors to agricultural damage. Simultaneously, the TITCI framework successfully decoupled typhoon intensity (TITCI-I) from hazard types (TITCI-T), as shown in Figure 4. For stations exhibiting high wind speeds and moderate rainfall, the TITCI-T yielded positive values, effectively identifying wind-dominant signatures across varying geographical locations. The TITCI-I component served as a robust indicator for typhoon magnitude, with higher positive values indicating severe integrated wind-rain impacts.

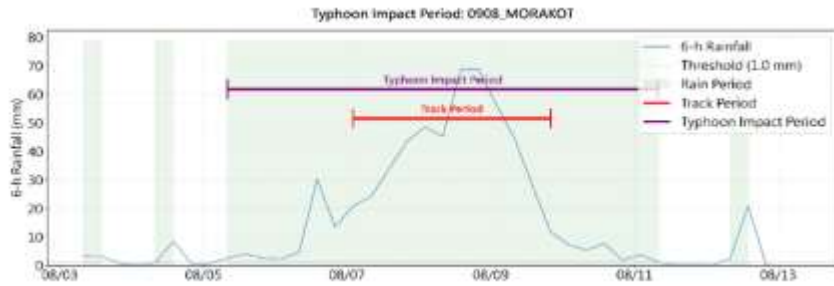


Figure 3. Illustrative example of the reconstruction of typhoon impact periods during Typhoon MORAKOT (2009)

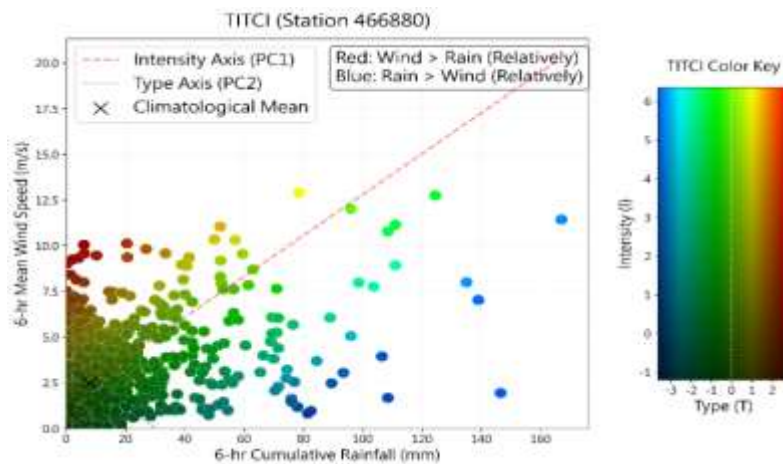


Figure 4. TITCI of specific stations

3.2 Visualization of dynamic and static input tensors

The gridded representations provided a spatially continuous meteorological field for the deep learning architecture. The alignment between static environmental constraints and the dynamic meteorological tensors ensures that the model perceives the spatial overlap between extreme weather and major agricultural production areas. Figure 5 displays the three static features (Agricultural Mask, DEM, and County Mask), while Figure 6 illustrates the four dynamic features (Rainfall, Wind Speed, TITCI-I, and TITCI-T). Notably, the TITCI-T successfully localized the extreme rainfall signatures in Southern Taiwan during Typhoon MORAKOT, whereas the mechanical destruction potential of Typhoon SOUDELOR was clearly captured by high TITCI-I values.

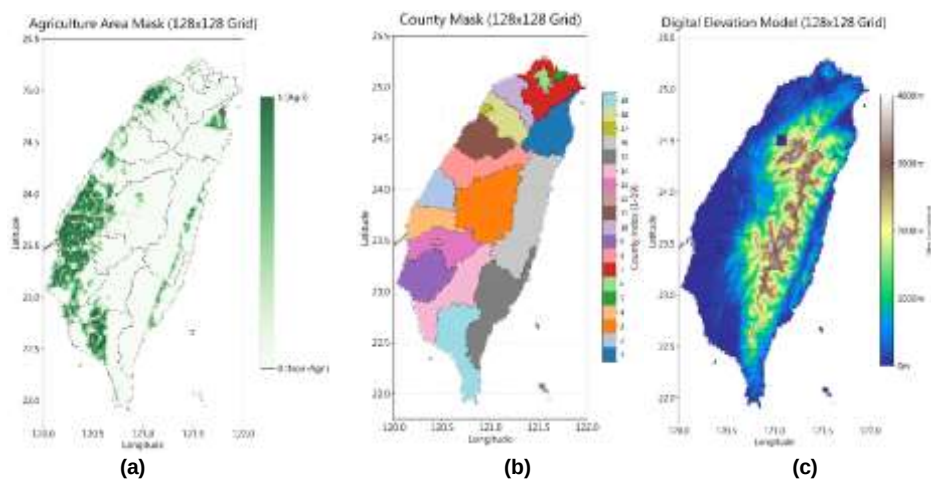


Figure 5. Gridded static feature (a) Agriculture area, (b) County identification, and (c) Digital Elevation Model

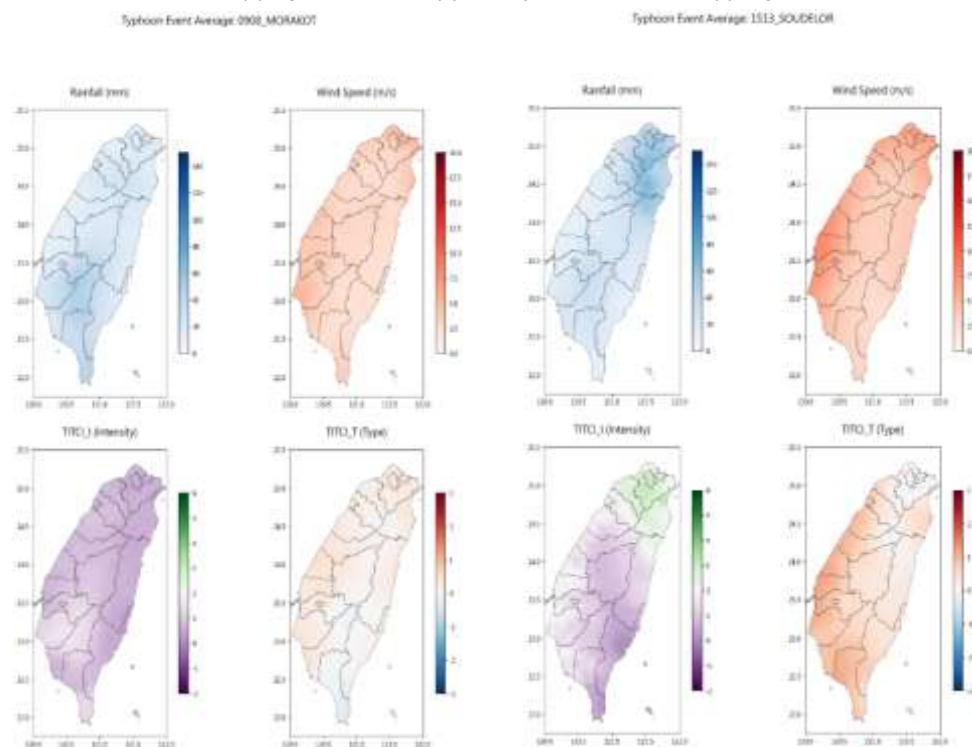


Figure 6. Dynamic features (average results) (a) 2009 Typhoon MORAKOT (b) 2015 Typhoon SOUDELOR

3.3 CNN-ConvLSTM predictive performance

The CNN-ConvLSTM model demonstrated stable convergence, achieving a final test MAE of 1.4290 in log-transformed space (equivalent to approximately 16.64 million TWD). To mitigate the raw underestimation bias without distorting log-space distributions, a median-based post-calibration scale factor (68.54×) was applied. The calibrated model achieved an ideal alignment ratio of 1.00 for the most catastrophic interval (>1,000 thousand TWD), with median prediction ratios across lower damage intervals ranging from 0.06 to 1.55 (Table 1).

Table 1. Comparison of actual, uncalibrated and calibrated predicted medians across damage intervals in the test set

Damage Interval (Thousand NTD)	Sample Size (N)	Actual Median Thousand NTD)	Calibrated	
			Predicted Median (Thousand NTD)	Alignment Ratio (Pred / Actual)
< 10	5	7	0	0.06
10 – 100	25	37	20	0.53
100 – 1,000	100	395	613	1.55
> 1,000	300	13294	13306	1.00

To evaluate the model's ability to localize agricultural damage, the 95-dimensional output vectors were projected back onto the 128 × 128 geographic grid (Figure 7). The model successfully identified major damage hotspots in Southern Taiwan, exhibiting high spatial correlation across primary crop categories. This confirms that the architecture successfully learned the complex interactions between TITCI meteorological signatures and static topographical constraints. As summarized in Table 2, high-value crops (fruit trees and vegetables) exhibited the highest mean spatial alignment ($r = 0.525$), indicating greater environmental sensitivity to the captured meteorological features than staple grains. More significantly, to evaluate the model's event-level predictive capability, Spearman's Rank Correlation Coefficient were computed across the 17 test typhoon events, which reached an impressive 0.7842 ($p=0.0001$), indicating performance particularly well in monotonic ranking.

4. DISCUSSION

4.1 Spatial correlation and data reporting constraints

The observed mean Pearson correlation (approximately 0.46) reflects the spatial heterogeneity of agricultural landscapes and the complexities of ground-truth data collection. Since the official crop disaster dataset relies on a bottom-up reporting mechanism, factors such as reporting delays, missing records, or varying local verification standards introduce significant spatial noise. Consequently, raw reports often appear fragmented and spatially discontinuous, as illustrated in Figure 8.

In contrast, the CNN-ConvLSTM model generates a more spatially continuous hazard field. This suggests that the model's output can serve as a Potential Risk Map, identifying potential vulnerability zones that may have been underreported. Previous studies utilized NDVI and satellite imagery (e.g., Sentinel-1) for objective damage estimation (Fengjin & Qiufeng, 2023; Kumar, 2025; Kurihara et al., 2025). However, applying these in Taiwan is challenged by the high fragmentation of small-scale family farms. Future research should aim to integrate multi-temporal remote sensing data with deep learning models to validate ground-truth reports and further improve predictive accuracy across diverse farming scales.

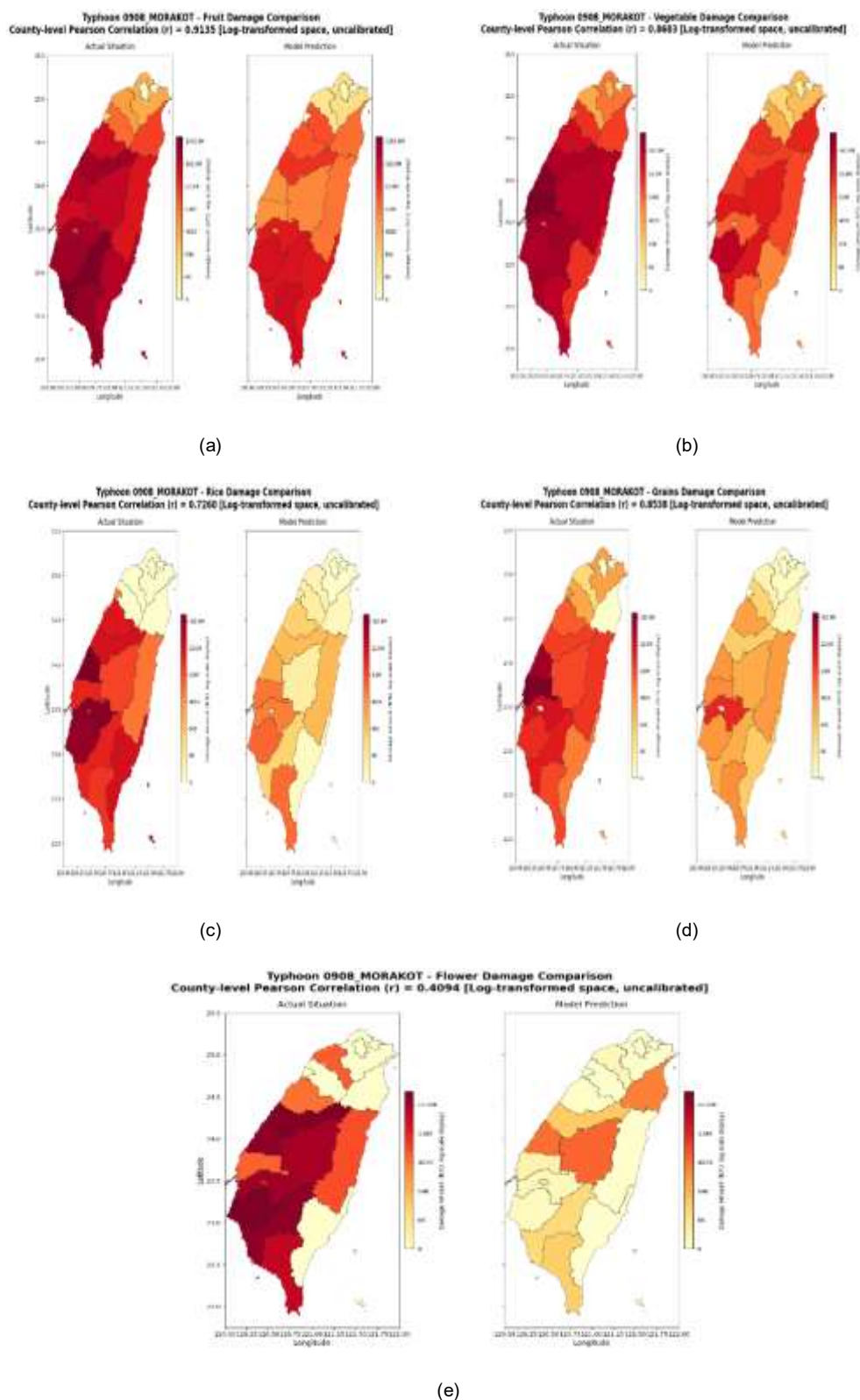


Figure 7. Spatial comparison of actual and predicted agricultural losses for Typhoon MORAKOT (2009).

Table 2. The spatial Pearson correlation coefficients across different crop categories

Crop category	Valid Mean Spatial Pearson correlation	Valid Events / Total
Fruit trees	0.525	14/18
Rice	0.355	11/18
Vegetable	0.525	13/18
Grains	0.447	13/18
Flower	0.470	9/18

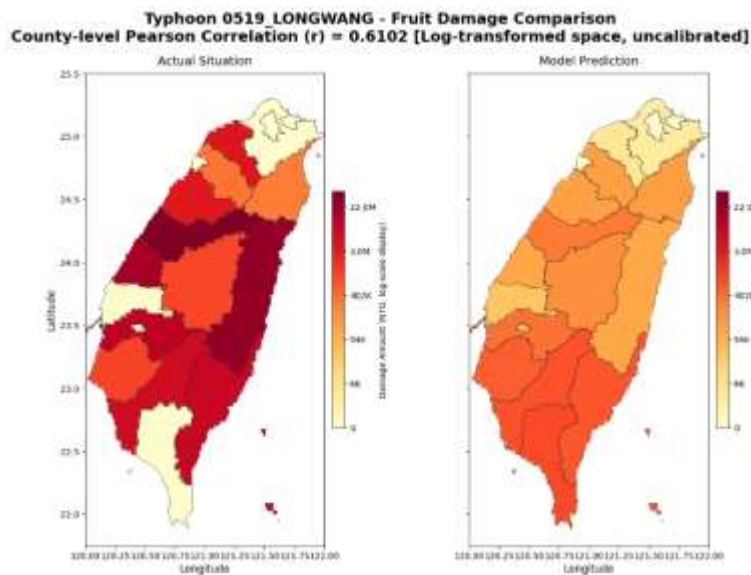


Figure 8. Spatial distribution comparison between administrative damage records and model predictions.

4.2 The role of CNN-ConvLSTM

The framework demonstrates superior predictive ability for catastrophic events like Typhoon MORAKOT (2009), where meteorological signals are dominant and widespread. The model's ability to accurately capture the magnitude of high-impact disasters represents a significant advancement for early warning systems. Furthermore, to address the scarcity of extreme event samples, a common challenge in disaster modeling, the incorporation of L2 regularization effectively promotes feature sparsity, ensuring the model remains focused on the most influential meteorological signatures without overfitting. Identifying localized impacts for weaker typhoons remains a challenge due to micro-scale factors, such as individual crop protection measures or local drainage efficiency, that are not captured by the county-resolution meteorological inputs. This limitation is further reflected in the model's calibrated predictions, which underperform in the lowest damage interval (<1,000 TWD), where the alignment ratio drops to 0.06. Moreover, the log-transformation also compresses signals at near-zero values, reducing sensitivity in this range during optimization. The model is therefore best interpreted as a strategic tool for prioritizing high-impact disaster response rather than a precise estimator of agricultural losses.

5. CONCLUSION

This study successfully establishes a Potential Risk Map by integrating TITCI physical indexing with a CNN-ConvLSTM integrated architecture. By utilizing PCA-based feature engineering, TITCI effectively overcomes the limitations of traditional discrete typhoon classifications, providing a continuous and comprehensive representation of typhoon characteristics. Simultaneously, the CNN-ConvLSTM model

captures the spatiotemporal evolution and cumulative effects of meteorological features, which are critical for assessing prolonged hazard exposure. Experimental results demonstrate that the framework not only accurately predicts damage for staple crops like rice but also provides precise potential loss estimations for high-value categories, including fruit trees, vegetables, grains, and flowers. This predictive capability is particularly evident in large-scale events that affect the entirety of Taiwan, such as Typhoon MORAKOT (2009). By translating log-transformed predictions back into monetary units, the model provides an actionable baseline for identifying vulnerability zones across 19 counties.

Ultimately, this research serves as a critical tool for early agricultural warning systems, enabling government authorities to allocate emergency resources more effectively based on data-driven potential loss assessments. Future work will focus on incorporating Satellite Remote Sensing data to provide objective spatial validation and further refine the accuracy of ground-truth reporting mechanisms.

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